TEMPORAL ADAPTIVE FILTERING OF SAR IMAGE TIME SERIES BASED ON THE DETECTION OF STABLE AND CHANGE AREAS

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ABSTRACT

This paper presents a novel multitemporal filtering approach for Synthetic Aperture Radar (SAR) images. This is a temporal adaptive filter for a time series of SAR images based on coefficient of variation test to detect stable areas and change areas. The proposed approach is illustrated on a time series of 25 ascending TerraSAR-X images acquired from 11/06/2009 to 09/25/2011 over Chamonix-MontBlanc test-site which includes different kind of changes: parking occupation, glacier surface evolution, etc.

1 Introduction

The launch of new generation satellites makes it possible to obtain time series of Synthetic Aperture Radar (SAR) images with short repeat cycle (11 days for TerraSAR-X) and high resolution (to 1-m with TerraSAR-X). The information of these time series is very useful for many applications, in particular for change detection and monitoring. One of the most important problems of SAR data is speckle noise involved in coherent acquisition systems, which makes it difficult for both human and automatic interpretation. With multitemporal data, both spatial and temporal information can be employed and this can yield improve results for filtering SAR data and then, other applications.

In the literature, there are a lot of multi-temporal filtering approaches such as texture-compensation multichannel filter (Bruniquel and Lopes) [1], multi-temporal speckle filtering of Quegan et al [2], time-space filter (Coltuc et al) [3], three-dimensional adaptive-neighborhood filter (Ciuc et al) [4], etc. Most multi-temporal filtering approaches have an assumption that spatial pixels remain unchanged over the time and all of the pixels at the same spatial coordinate in the time series are involved in the filtering procedure (averaging intensity/amplitude values for instance). This can be acceptable for some cases such as homogeneous fields, constructions, etc. in short periods, but it is not true for heterogeneous regions and leads to the radiometric degradation in filtered images. In general, this assumption is not appropriate with the fact that the ground features are not stable in all images of the time series, particularly in a long-period time series. To overcome this problem, in this paper, we propose a novel approach for temporal adaptive filtering of a time series of SAR images based on the detection of stable areas and change areas. The decision of stable and change areas is derived by applying coefficient of variation (CV) test.

2 Temporal adaptive filtering

2.1 Filtering strategy

Considering a time series of N co-registered SAR images, the proposed approach is made up of a processing chain including three steps (see Figure 1):

1) The first step is bi-date analysis: In each pixel pile, coefficient of variation tests are taken between each two dates using spatial windows. The result of this step is a cross test matrix (CTM1) in which, homogeneous pixels corresponding to reference dates are determined.

2) The second step is multidate analysis: Based on the result of the first step, coefficient of variation tests are taken between all the homogeneous pixels identified in the first step corresponding to a certain date and all homogeneous pixels corresponding to another date in the pixel pile. The result of this step is another cross test matrix (CTM2) which provides us stable and change pixels more accurately.

3) The last step is multitemporal filtering: Temporal mean is then applied by taking into account all the stable pixels corresponding to each date to derive filtered images.

2.2 Coefficient of variation test

Coefficient of variation (CV) test mentioned in section 2.1 aims at defining homogeneous pixels in the time series.

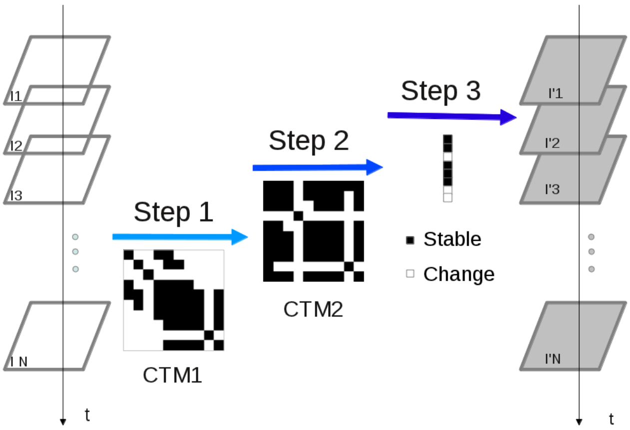


Figure 1: Processing chain of the proposed approach (Step 1: Bi-date analysis; Step 2: Multi-date analysis; Step 3: Temporal filtering)

Let us consider an $L-$looks amplitude image $\mathcal{I}$ at pixel position (i, j):

$$\mathcal{I}(i, j) = \rho(i, j).s(i, j) \tag{1}$$

where, $\rho(i, j)$ is the speckle-free image and $s(i, j)$ is the speckle noise. Standard deviation of speckle noise in purely homogeneous area is $\sigma_s = \frac{0.5227}{\sqrt{L}}$. The CV is denoted as the ratio of standard deviation to the mean of corrupted image.

$$CV = \frac{\sigma_{\mathcal{I}}}{\mu_{\mathcal{I}}} \tag{2}$$

If the ground surface is purely homogeneous, then $CV = \sigma_s$; on the contrary, if it varies, $CV > \sigma_s$. CV can, thus, be a test to estimate the homogeneity of the ground surface reflectivity.

In this paper, we adopt the local CV as the homogeneity test criterion and adaptive threshold:

$$CV(i, j) \leq \sigma_s + \delta \tag{3}$$

where δ is a small value added to σ_s as a tolerance of the threshold and derived from [5]. Hence, the adaptive threshold is denoted:

$$T(i, j) = \eta \left(\sigma_s + \sigma_s \sqrt{\frac{1 + 2\sigma_s^2}{2n}} \right) \tag{4}$$

in which, n is the number of elements involved in the CV test, η is a system parameter that determines the degree of smoothing. In general, the values of η are around 1.0

In the next sections, we will describe steps of the processing chain into detail.

2.3 Bi-date analysis

At each pixel position, we have a pixel pile of the time series. Let $\mathcal{I}_{i,j,t}$ be the element located at the (i, j) pixel of image $\mathcal{I}_t$ acquired at date t of the time series and

$$\mathcal{I}[i, j, t, r] = \{\mathcal{I}_{i+p,j+q,t}\}_{-r \leqslant p \leqslant r, -r \leqslant q \leqslant r, 1 \leqslant t \leqslant N} \tag{5}$$

be the centered pixel of a $(2r + 1) \times (2r + 1)$ analysis window which determines the boxcar neighborhood of $\mathcal{I}_{i,j,t}$ concerned by the local CV.

In this step, we test the homogeneity between each two pixels of two dates in the pixel pile, so that we need to use a spatial neighborhood of each pixel concerned in the test to estimate local statistic. The CV test in this step is defined as:

$$CV(\mathcal{I}[i, j, m, r], \mathcal{I}[i, j, l, r]) \leqslant T(i, j) \tag{6}$$

where, m and l are the acquisition dates (they are denoted as t in Equation 5). The locus of all the responses given by the test (6) forms the *cross test matrix 1 (CTM 1)*. If $\mathcal{I}[i, j, m, r]$ is homogeneous to $\mathcal{I}[i, j, l, r]$, then the test response is 0, else the test response is 1. $CTM1$ is a symmetric matrix.

2.4 Multidate analysis

In order to refine the result of stable/change pixel determination in each pixel pile derived from step bi-date analysis, we test again the CV but with multidate images instead of bi-date images as the previous step.

Let $\mathcal{T}_1\{[i, j, m], u\}$ and $\mathcal{T}_1\{[i, j, l], v\}$ be the sets of homogeneous pixels determined in $CTM1$ corresponding to $\mathcal{I}[i, j, m, r]$ and $\mathcal{I}[i, j, l, r]$, respectively. Where, u and v are numbers of elements in set $\mathcal{T}_1\{[i, j, m], u\}$ and $\mathcal{T}_1\{[i, j, l], v\}$, respectively, and $1 \leqslant u \leqslant N$, $1 \leqslant v \leqslant N$.

In this step, we investigate two cases:

1) For homogeneous regions, the CV tests are implemented with spatio-temporal information of the time series;

2) For isolated targets, only temporal information is used. The CV test in this step is denoted as:

• For case 1:

$$CV(\mathcal{T}_1\{[i, j, m, r], u\}, \mathcal{T}_1\{[i, j, l, r], v\}) \leqslant T(i, j) \tag{7}$$

• For case 2:

$$CV(\mathcal{T}_1\{[i, j, m], u\}, \mathcal{T}_1\{[i, j, l], v\}) \leqslant T(i, j) \tag{8}$$

The result of this step is the *cross test matrix 2 (CTM 2)* which is established in the same way as $CTM1$.

2.5 Temporal mean filtering

Matrix $CTM2$ provides us stable and change pixels in each pixel pile. Let $\mathcal{T}_2\{[i, j, t], n\}$ be the set of homogeneous pixels determined in $CTM2$ corresponding to $\mathcal{I}_{i,j,t}$, where, n is number of elements in set $\mathcal{T}_2\{[i, j, t], n\}$ and $1 \leqslant n \leqslant N$.

The filtered image $\hat{\mathcal{I}}_{i,j,t}$ is derived as following:

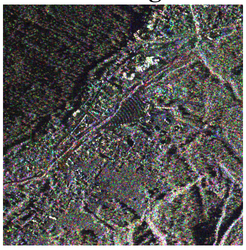
$$\hat{\mathcal{I}}_{i,j,t} = \frac{1}{n} \sum_{k=1}^{n} \mathcal{I}_{i,j,k} \mid \mathcal{I}_{i,j,k} \in \mathcal{T}_2\{[i, j, t], n\} \tag{9}$$

3 Experimental results

3.1 Test-site data

The proposed approach is illustrated on a time series of 25 single look complex ascending TerraSAR-X images acquired from 11/06/2009 to 09/25/2011 over Chamonix-MontBlanc with 2-m resolution. We study two small test-sites: a parking area (Grands Montets) and a moving glacier (Argentière) which its surface moves about 20 cm per day, so more than one pixel between two consecutive dates in the time series. The two test-sites include different kind of changes: parking occupation, glacier surface evolution, etc.

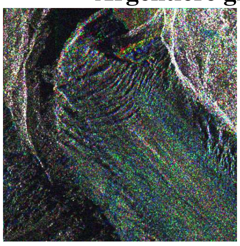
Parking Grands Montets test-site



(a) RGB composition image

(b) Optical image

Argentière glacier test-site



(c) RGB composition image

(d) Optical image

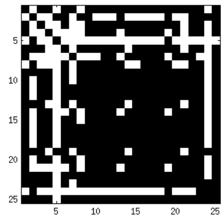
Figure 2: Chamonix-MontBlanc test-site (R: 2011/06/07; G: 2011/06/18; B: 2011/06/29)

3.2 Temporal adaptive filtering results and remarks

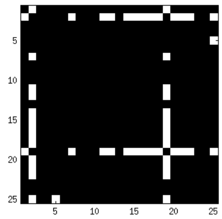
In this paper, we apply the minimum analysis window (including the central pixel and its four nearest neighborhood pixels) when using spatial information. For homogeneous regions such as grass, Figure 3 a and b show that the proposed filtering operator can detect stable pixels in each pixel pile effectively. They also prove that even in homogeneous area, it is not true to consider that all the pixel in a pixel pile are stable. $CTM2$ detects more stable pixels than $CTM1$ does. The profile of filtered time series in Figure 3 is quite correlated to the one of original time series but the dynamic range of amplitude pixel values in filtered time series are reduced due to the averaging process in step 3 of the proposed method, and it also reduces speckle noise significantly.

In the case of isolated target such as a car in the parking: there is only one date (one image) in which, an object appears at a certain location. The pixel at the object location of that date is completely different from other pixels in the pixel pile. In the filtered image of that image, pixel value of the object is preserved as illustrated in Figure 4.

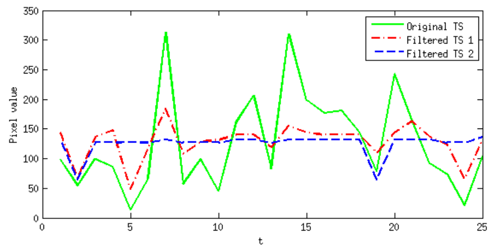
Looking into Figure 5, the reduction of speckle in filtered image helps us to see clearly details of the parking with small cars, which cannot be distinguished in the original image. Figure 6 reveals another interesting point of this filter: it removes well speckle in stable areas but it almost avoids filtering moving areas. The effect of filtering is presented obviously in the rock area, but at the glacier area, original and filtered images look quite similar. The cause of it is that at this area, glacier pixel values in the time series changes from date to date and each point on this surface moves more than one pixel between different acquisitions. Therefore, the filter which is based on averaging stable pixels detects very few stable samples for averaging process.



(a) $CTM1$



(b) $CTM2$



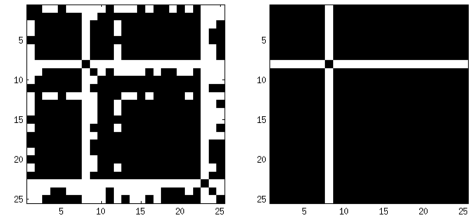
(c) Profiles of original time series, and filtered time series based on $CTM1$ and $CTM2$

Figure 3: Cross test matrix and temporal profiles for a pixel in a homogeneous region (grass)

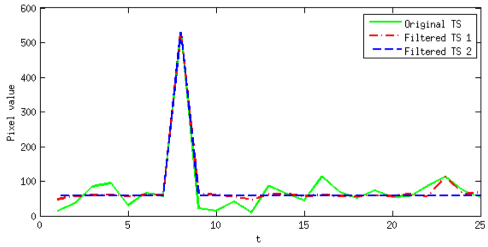
To assess the filtering performance in terms of speckle reduction, the equivalent number of look (ENL) of filtered images are presented in Table 1. They increase significantly in comparison with original images, with even stronger speckle reduction after step 2.

4 Conclusions and perspectives

In this paper, a new method of filtering SAR image time series is presented. The proposed filter is based on coefficient of variation test to determine stable and change pixels in each pixel pile of the time series. The experimental results have shown that the proposed approach reduces speckle significantly while preserving detail features, edges and changes, etc.. The filter has very little impact on moving areas. This advantage allows to filter images including stable and moving areas without losing characteristics of moving areas which are very important in monitoring their



(a) $CTM1$ (b) $CTM2$



(c) Profiles of original time series and filtered time series based on $CTM1$ and $CTM2$

Figure 4: Cross test matrix and temporal profiles for a pixel at isolated target (a car in the parking)

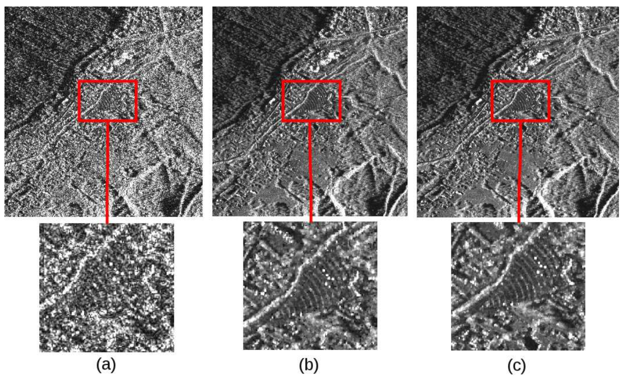


Figure 5: Filtering results at parking test-site. (a) Original image (08/27/2009); (b) Filtered image using $CTM1$; (c) Filtered image using $CTM2$

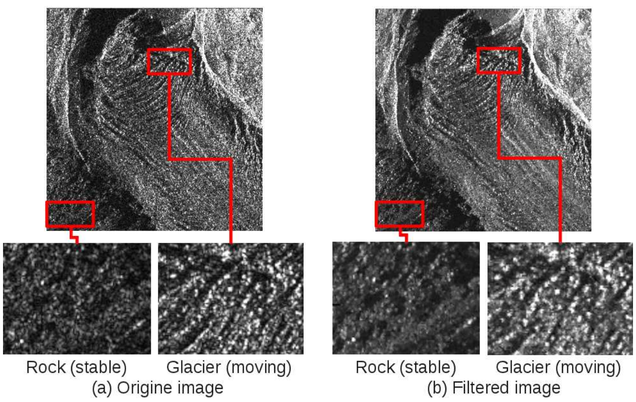


Figure 6: Filtering results at glacier test-site, image acquired on 03/09/2011

Table 1: Equivalent number of look of the time series computed in homogeneous areas

No	ENL of original image	ENL of filtered image (using CTM 1)	ENL of filtered image (using CTM 2)
1	0.9341	10.8239	12.4390
2	0.8936	10.2763	12.2835
3	0.8765	10.6405	13.5580
4	0.8824	10.4012	13.6410
5	0.8524	9.8827	12.4541
...	...	...	...
10	0.9323	10.9148	13.3715
11	0.9432	10.2172	10.7973
12	0.8725	9.4786	13.8458
13	0.9202	10.0371	13.4212
14	0.9303	10.6556	12.3830
...	...	...	...
20	0.9730	10.5930	11.8362
21	0.9481	10.6918	11.3806
22	0.9187	10.4997	13.5367
23	0.9425	10.3891	13.4048
24	1.0228	11.4888	12.9309
25	0.8825	10.2899	13.2800
Mean	**0.9290**	**10.5530**	**12.7698**

evolution (glacier for instance) and simultaneously reduces speckle at other areas of images.

The further works of this approach may concern: developing an automatic test for purely temporal or spatiotemporal neighborhood and analyzing multitemporal change in a time series.

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